

# Artificial intelligence in a communication system for air traffic controllers' emergency training

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## Article Info

### Article history:

Received Aug 30, 2021

Revised May 26, 2022

Accepted Jun 9, 2022

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### Keywords:

Air traffic control

Automatic speech recognition

Convolutional neural networks

Emergency services

Phraseology

Recurrent neural networks

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## ABSTRACT

In the last few years, there has been a lot of research into the use of machine learning for speech recognition applications. However, applications to develop and evaluate air traffic controllers' communication skills in emergency situations have not been addressed so far. In this study, we proposed a new automatic speech recognition system using two architectures: The first architecture uses convolutional neural networks and gave satisfactory results: 96% accuracy and 3% error rate on the training dataset. The second architecture uses recurrent neural networks and gave very good results in terms of sequence prediction: 99% accuracy and  $e^{-7}$ % error rate on the training dataset. Our intelligent communication system (ICS) is used to evaluate aeronautical phraseology and to calculate the response time of air traffic controllers during their emergency management. The study was conducted at International Civil Aviation Academy, with third-year air traffic control engineering students. The results of the trainees' performance prove the effectiveness of the system. The instructors also appreciated the instantaneous and objective feedback.

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## 1. INTRODUCTION

Maintaining and improving human performance can only be achieved by focusing training on the skills needed to perform their duties safely and effectively, and if the training involves a variety of scenarios that expose people to the most relevant threats and errors in their environment. Human error is frequently cited in air accident investigation reports as a major cause of accidents and serious incidents, despite the evolution of the technologies and safety systems used [1]. Security is therefore only possible through practical training that makes error less probable and their consequences less serious. When an aviation emergency is declared, it is mandatory to think quickly and act immediately [2]. However, the need to communicate effectively and in a timely manner, as well as the lack of qualified personnel and time, causes stress that impairs the air traffic controller's situational awareness and decision making and can lead to serious incidents: 60% of communication errors between pilots and controllers are the cause of accidents or incidents [3]. According to a study by NASA's aviation safety reporting systems (ASRS) database, Incorrect controller -pilot communication is a causal factor in 80% of aviation incidents or accidents, while late communication accounts for 12% of the causes leading to incidents or accidents, as shown in Table 1 [4].

Table 1. Communication factors [4]

Factor	Percentage of Reports
Incorrect communication	80%
Absence of communication	33%
Correct but late communication	12%

In order to reduce communication errors and ensure redundancy of communications between the controller and the pilot, the International Civil Aviation Organization (ICAO) has established a confirmation and correction process as a defence against communication errors [4], as shown in the Figure 1. However, in an abnormal or emergency situation (ABES), where every second counts, this communication loop can only be effective if the aeronautical phraseology used is correct and standard. Communication errors and the waste of time repeating messages in this kind of stressful situation can have tragic consequences.

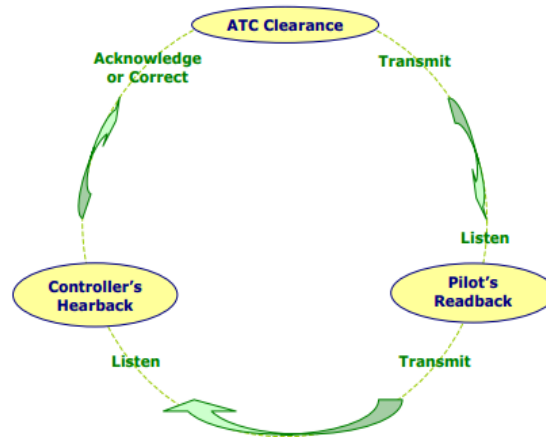


Figure 1 . Controller-pilot communication loop [4]

Traditionally, the performance of trainee air traffic controllers is assessed on simulators by requiring the presence of pseudo-pilots. Figure 2 illustrates the whole controller/pseudo-pilot communication process and associated devices [5]. However, the evaluation of performance during an emergency or abnormal situation (aircraft engine failure in our scenario) should not only determine whether the communication has been made but also whether the aeronautical phraseology is used correctly and in a timely manner. This can only be achieved by designing new systems that can perform an instantaneous and objective assessment of air traffic controllers' verbal communication.

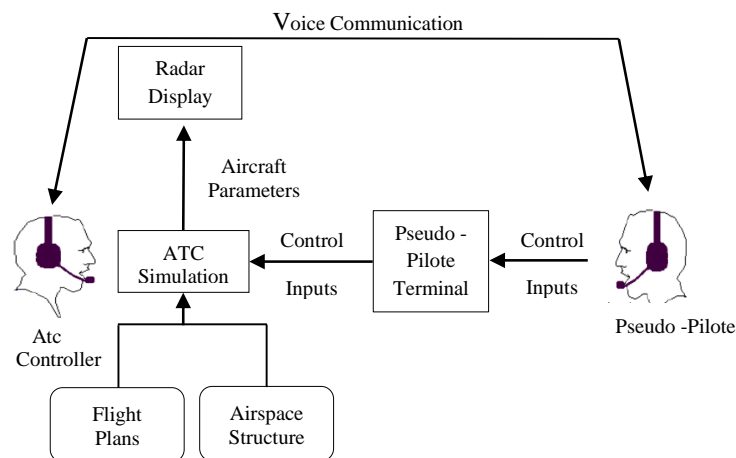


Figure 2. Controller/Pseudo-pilot communication [5]

Deep learning algorithms have mainly been used to improve the computer's capabilities to understand human behaviour, including speech recognition [6]. With the introduction of artificial intelligence [7], [8] speech recognition has in fact received a lot of attention in recent years and is proving to be an excellent tool for the analysis of instantaneous phraseology in an Air traffic controllers (ATC) simulator environment by replacing pseudo-pilots with an automatic speech recognition device [9]. It is therefore interesting to implement new interactive systems based on automatic speech recognition that allow the evaluation of air traffic controllers' communication skills, especially when they are confronted with stressful situations [10]. Our present study thus aims to propose a new intelligent communication system based on automatic speech recognition that should recognise the phraseology errors made in real time by student air traffic controllers when faced with ABES.

To achieve this, we organise our present paper as follows: section 1 gives an overview of the proposed system, while section 2 presents the creation of an intelligent speech recognition architecture using convolutional neural networks (CNN) and recurrent neural networks (RNN). The results and performance are described in section 3. Finally, section 4 concludes our research work.

## 2. RESEARCH METHOD

### 2.1. Overview of the proposed system

ATC are trained to use standard and correct International Civil Aviation Organisation (ICAO) phraseology. However, it has been observed that many air traffic controllers can work for long periods without being exposed to ABES. This lack of practice changes the aeronautical phraseology used without the air traffic controller being aware of it. To address this lack of practice, it was decided to develop a new system based on automatic speech recognition technology that allows interaction between the student and the machine without the need for a second person to perform the pseudo-pilot task. The speech recognition function will serve as a basic tool for improving the quality of the evaluation. The user's willingness to move on to the next phase will be instantaneous. In addition, a time function has been integrated into the proposed system in order to determine the overall duration of the performance. The process chain can thus be described as illustrated Figure 3.

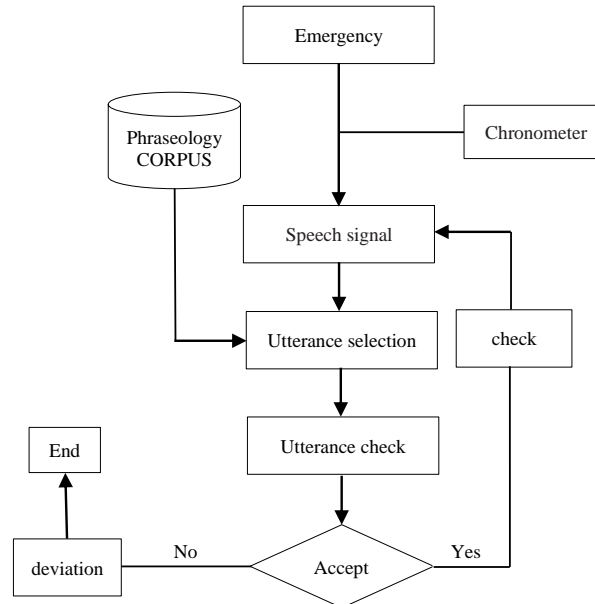


Figure 3. Flowchart describing

The following rules will be used to assess performance. It should be noted that this is an aircraft engine failure event:

- Each emergency activation is a consequence of detecting the term "Emergency". The "Emergency" expression is the event that triggers the emergency situation.
- Once an emergency has been activated, a chronometer is set up to calculate the time spent in the whole emergency exercise. Time pressure is an essential element of emergency management. Wasting time

repeating messages and finding the correct phraseology to be understood will reduce the efficiency of the air traffic controller, cause misunderstandings and will not ensure pilot confidence in the service provided.

- The input to the system is the student's speech and a list of predicted phraseology from the newly designed phraseology corpus. The corpus contains (so far) thirty-six transcripts from twelve students (seven female and five male) who were asked to participate in three different scenarios: i) loss of separation between two aircraft during initial climb due to engine failure; ii) failure of ground-to-air communication; and iii) overflying a restricted area due to bad weather conditions. The students' communications were conducted in English, the official and most widely used language in aviation [11].
- The student's speech is compared to the word sequences in the corpus to detect errors. If the answer is not accepted, the student is invited to try again.
- Each passage between the phases is the consequence of detecting the term "check".
- The chronometer will always remain on while the practical exercise is in progress. The total time of the simulation will be a decisive factor in assessing the student's performance.

**2.2. Data**

**2.2.1. Features extraction**

Poor quality or erroneous data can lead to difficulties in extracting information and making wrong predictions, so data must be properly prepared and collected. Features extraction is generally referred to as front-end signal processing [12]. Feature extraction techniques typically produce a multidimensional feature vector for each speech signal [13]. It is noted that speech features play an essential role in separating one speaker from another [14]. The extraction of features reduces the magnitude of the speech signal in a way that does not damage its power [15]. In our research, this is the first step that each of the recording files will go through. It consists of the transformation of one-dimensional audio data into three dimensional spectrograms after extraction of vectors characteristic of each vocal signal.

There are a variety of different options for representing the speech signal for the process of recognition, Mel-frequency cepstral coefficient (MFCC) is the most popular [16]. The particularity of the transformation into MFCC is is that even more accuracy is obtained by increasing the size of the acoustic characteristic vectors, or by increasing their number. That is by increasing the number of MFCC coefficients.

**2.2.2. MFCC**

MFCC are cepstral coefficients calculated by a discrete cosine transformation applied to the signal's power spectrum. The frequency bands of this spectrum are logarithmically spaced along the Mel scale. The MFCC computation is the replication of the human auditory system that aims at an artificial implementation of the working principle of the ear, assuming that the human ear provides a reliable means of speaker recognition [17]. In our research, these coefficients are obtained by the following stages as illustrated in Figure 4 [15]:

- Cut the signal into "frames".
- Apply the Fourier transform to the acoustic signal corresponding to each frame to obtain the frequency spectrum of each signal.
- Apply a logarithmic filter to the obtained spectrum as illustrated in (1) :

$$Mel(f) = 2595 \times \text{Log}(1 + f700) \tag{1}$$

- Reapply a Fourier transform to a cosine.

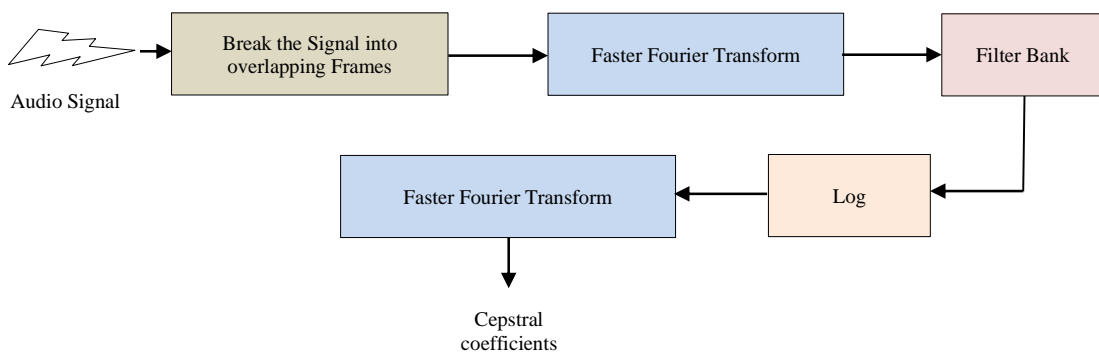


Figure 4. Mel-frequency cepstral coefficient [15]

The idea is to have a correspondence between the set of transformed speech and the set of words that we want our system to be able to identify, in particular: the expression "emergency" to trigger the exercise of the emergency situation and the expression "check" for the inter passage between two successive steps of the emergency management procedure (engine failure in our example). In addition, in order to avoid making the system reactive to noise, a third class has been added, grouping a number of noise patterns that may exist in the working environment of an ATC simulator. This set could only be completed by a set of "Labels" consisting of the images of the words corresponding to each speech via the tilde application  $\sim$ . The established bijection, of the set of "Labels" of: i) emergency, ii) control, and iii) noise, is represented in (2):

$$\sim: \left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} \right\} \rightarrow \{\text{emergency, check, noise}\} \quad (2)$$

Our training dataset is now complete. A formalisation of the dataset is presented as shown in (3):

$$\text{dataset} = \left\{ \left( [[\text{Mel}(f_i)]^{n_{mel}}]_{k'} \sim (g_k) \right) \text{ tel que } k \in [0; \text{taille} - 1] \right\} \quad (3)$$

$f_i$  : Frequency of frame  $i$  ;  
 $n_{mel}$  : Number of frames treated;  
 $g_k$  : Grammar corresponding to the  $k$  element.

### 2.3. Creation of an intelligent speech recognition architecture

In the last few years, the performance of deep learning algorithms has surpassed that of traditional machine learning algorithms. The most commonly used deep learning algorithms in the field of speech recognition are RNN and CNN [18]. CNNs have many applications in video and image recognition and recommendation systems [18], [19]. Mathematically, a convolution is the combination of two functions to obtain a third function. The inputs are reduced to a form without loss of features, thus reducing the computational complexity and increasing the success rate of the algorithm [20].

RNN are a family of neural networks specialised in processing sequential data. They can remember the input data received and predict precisely what will follow. Due to their nature, RNNs are successfully applied to sequential data such as time series, speech, video, and text [21]. Through the use of a long and short term memory architecture, the RNN is able to access long term memory. Long short term memory (LSTM) RNNs are a sort of gated RNNs which provide the most efficient models used in practical applications and solve the long-term dependency problem of RNNs [22].

During the project, we tested different architectures, which gave different results: the first architecture uses CNNs and gave satisfactory results: 96% accuracy and 3% error rate on the training dataset. The second is a recursive approach, using RNNs, which is notably good in terms of sequence prediction: 99% accuracy and  $e^{-7}$  % error rate on the training dataset. The architectures used for the two kinds of models described are respectively as listed in Figure 5.

### 2.4. Training

After creating the model's brain, the collected data will be used to find a value for the parameters of the model that will allow it to properly perform its recognition task. The training of the model is done in our case using a well-known technique in optimization: the gradient descent [23], [24]. A neural network is a set of calculating stages where formatted data will enter and be transformed in order to extract characteristics. This transformation will be done by means of weights and by the successive application of two mathematical operations: a linearity and a non-linearity [25]. The hyper-parameters of a model are first initialised with random values, then during training the output of the model will be calculated and compared to the expected value (from the dataset). The (4) represents the error terms obtained by deriving the error function with respect to each weight [26].

$$\forall i, j \quad \varepsilon_{ij} = |\Delta w_{ij}| = \left| \frac{\partial E}{\partial w_{ij}} \right| \quad (4)$$

$E$  : Error function;  
 $w_{ij}$  : Weights of the neural network;  
 $i, j$  : Error indices.

Thus, the network adjusts its weights after each data sample until a value closer to the ideal is obtained. This learning process is in fact the gradient descent algorithm which works as [27]:

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For each batch of data do:
    V = prediction_model(batch)
    U = Label_correct(batch)
    Err = E(V,U)
    For i,j indices of the Err matrix do:
         $\varepsilon_{ij} = |\Delta w_{ij}| = \left| \frac{\partial E}{\partial w_{ij}} \right|$ 
         $\varepsilon = [\varepsilon_{ij}]_{i,j}$  # weight correction matrix
    Correct weights ()
Next batch

```

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 124, 220, 64)	1664
max_pooling2d_1 (MaxPooling2D)	(None, 62, 110, 64)	0
conv2d_2 (Conv2D)	(None, 60, 108, 32)	18464
max_pooling2d_2 (MaxPooling2D)	(None, 30, 54, 32)	0
dropout_1 (Dropout)	(None, 30, 54, 32)	0
conv2d_3 (Conv2D)	(None, 28, 52, 16)	4624
max_pooling2d_3 (MaxPooling2D)	(None, 14, 26, 16)	0
dropout_2 (Dropout)	(None, 14, 26, 16)	0
flatten_1 (Flatten)	(None, 5824)	0
dense_1 (Dense)	(None, 10)	58250
dropout_3 (Dropout)	(None, 10)	0
dense_2 (Dense)	(None, 7)	77
dense_3 (Dense)	(None, 3)	24
Total params: 83,103		
Trainable params: 83,103		
Non-trainable params: 0		
Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 128, 128)	143488
conv1d_2 (Conv1D)	(None, 128, 64)	24640
conv1d_3 (Conv1D)	(None, 128, 128)	41088
conv1d_4 (Conv1D)	(None, 128, 128)	49280
conv1d_5 (Conv1D)	(None, 128, 128)	49280
bidirectional_1 (Bidirectional)	(None, 128, 40)	23040
flatten_1 (Flatten)	(None, 5120)	0
dense_1 (Dense)	(None, 7)	35847
dense_2 (Dense)	(None, 3)	24
Total params: 367,487		
Trainable params: 367,487		
Non-trainable params: 0		

Figure 5. The respective architectures of the CNN and RNN

### 3. RESULTS AND DISCUSSIONS

Our system can be considered as a real learning environment for the development of communication competence, for two main reasons: firstly, the analysis of phraseology is instantaneous thanks to speech recognition and secondly, the integration of the temporal constraint of performance to allow the simulation of the temporal pressure present in an abnormal and emergency situation. The existence of such a model provides a safe and non-threatening practice environment that tolerates trial and error. Most of the students did not perform well in communication in the first attempts: there were errors, disfluencies, hesitations in the messages conveyed and delays in communication. Some students reported feeling stressed at the beginning of the scenario because they had to use the correct phraseology and deal with an emergency situation at the same time. Figure 7 shows the average performance of a student for a single scenario repeated four times (engine failure in our example), in which they have to use correct aviation phraseology in a six-step engine failure management checklist as illustrated in Figure 6 [28].



Figure 6. Engine failure checklist [28]

The different pattern in Figure 7 indicate the student's performance in the six steps of the engine failure management exercise. The student's poor communication performance in the first two trials can be attributed to initial fear, use of incorrect aviation phraseology and unfamiliarity with the system. However, from the third repetition onwards, the student started to become familiar with the system and showed significantly better performance.

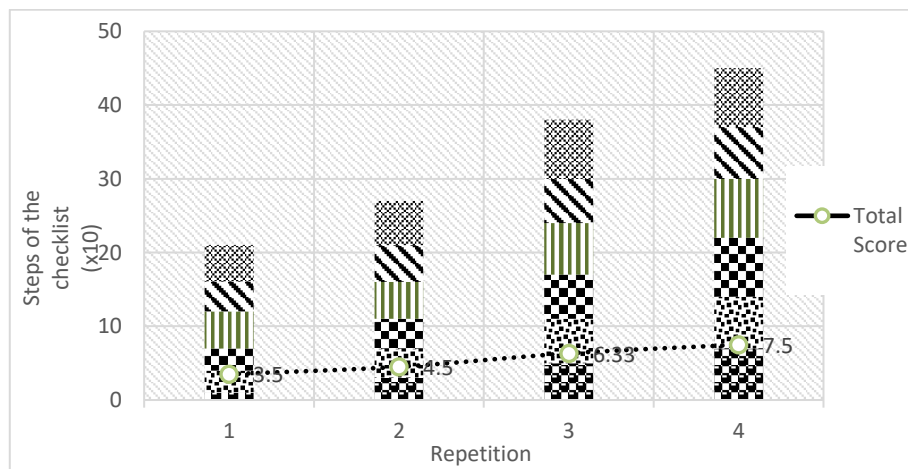


Figure 7. Performance monitoring

The students find the ICS is an effective for developing the ability to produce correct aeronautical phraseology, even under stress. However, the assessment of nonverbal communication such as speaker's postures and voice was not possible. Some students stressed the relevance of nonverbal communication in the communication process.

As there are few qualitative studies on the use of speech recognition to train soft skills, especially communication skills in the context of air traffic control, this study could add value to future research. However, one limitation of this study is that the speech recognition model will need even more data to achieve a higher accuracy value. Thus, our first recommendation for the future will be to spend much more time on data collection, data augmentation and data processing, in order to obtain a rich and high quality database.

#### 4. CONCLUSION

In order to ensure proper management of emergency situations, air traffic controllers must be prepared to deal with multiple information simultaneously by listening, understanding and using correct and standard aeronautical phraseology. Our study consists of proposing a ICS based on automatic speech recognition, allowing the interaction between the student and the machine without the need for a second student to perform the task of the pseudo pilot. In addition, the function of calculating the time taken to transmit instructions and clearances issued by student air controllers during emergency management was incorporated into the system. Through instant practice and repetition, the students were able to develop effective and efficient communication that facilitates emergency management. However, a limitation of this study is that the speech recognition model will still need more data. As the research is still in the development phase, future work is to develop a scalable training system that allows the injection of new scenarios.

#### ACKNOWLEDGEMENTS

We would like to thank the student air traffic controllers, without whom this research would not have been possible.

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